Buildings & Cities

A population-level framework to estimate unequal exposure to indoor heat and air pollution

SPECIAL COLLECTION: HEALTH INEQUALITIES AND INDOOR ENVIRONMENTS

RESEARCH

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ABSTRACT

As people in the UK spend 95% of their time indoors, buildings are an important modifier of exposure to both non-optimal temperatures and air pollution. High ambient temperature and high $PM_{2.5}$ (particulate matter) concentrations often occur together in urban areas. Residential building types prone to overheating (*e.g.* purpose-built flats) are often also more common in urban areas. Together, this may lead to spatial and demographic inequalities in indoor exposure to heat and $PM_{2.5}$ from outdoor sources. By combining building simulations (EnergyPlus), a spatially distributed description of the residential building stock—from publicly available Energy Performance Certificate (EPC) data, ambient temperature, $PM_{2.5}$ data and area-level (40–250 households) socio-demographic data—we estimated these inequalities in exposure for the population of England and Wales. Maximum indoor temperature was higher in areas with larger ethnic minority and infant populations, and lower in areas with a higher proportion of people aged ≥ 65 years. Indoor concentrations of outdoor-source $PM_{2.5}$ were higher in areas with larger ethnic minority and low-income populations. With rising inequality in England and Wales, housing and environmental conditions play an important role in contributing to health inequalities from social disadvantage.

POLICY RELEVANCE

Differences in environmental exposures may partly explain inequalities in health outcomes. These differences are mediated by dwelling type and quality. Identifying the driving factors for differences in environmental exposures may allow for the development of interventions to address health inequalities more effectively. This study finds differences in indoor exposure across socio-demographic groups due to both location and housing. This could be of interest to national, regional and local authorities responsible for targeting building retrofit interventions across the housing stock.

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KEYWORDS:
building design; deprivation; environmental health; health inequalities; housing; indoor air quality (IAQ); indoor pollutants; overheating; public health; vulnerability

TO CITE THIS ARTICLE:
Cole, R., Simpson, C. H., Ferguson, L., Symonds, P., Taylor, J., Heaviside, C., Murage, P., Macintyre, H. L., Hajat, S., Mavrogianni, A., & Davies, M. (2024). A population-level framework to estimate unequal exposure to indoor heat and air pollution. *Buildings and Cities*, 5(1), pp. 562–580. DOI: https://doi.org/10.5334/bc.425

1. INTRODUCTION

In the UK, the environmental threats of increasing ambient temperatures (Kendon *et al.* 2022) and air pollution concentrations that regularly exceed international guidelines (DEFRA 2019) pose a dual challenge to population health. Exposure to high ambient temperatures reduces thermal comfort, affecting people's sense of wellbeing, cognitive performance, productivity and sleep quality, as well as aggravating existing health conditions (including renal, respiratory and cardiovascular diseases) and, in some cases, leading to heat stroke (Kovats & Hajat 2008). Air pollution accumulates in urban environments from the combustion of solid fuels for residential heating, road transport and industrial processes, and is similarly associated with harms to health, including increases in respiratory and cardiovascular disease (Brunekreef & Holgate 2002). Both exposures have been associated with excess deaths. It is estimated that the population spends up to 95% of its time indoors (Smith *et al.* 2016), making buildings a key modifier of how individuals experience heat and air pollution events, and therefore housing is a key component of climate change-adaptation strategies (WHO 2018). Growing health inequalities in high-income countries, despite overall improvements in health outcomes across the population, have been in part attributed to variations in housing quality between different population groups (Wilkinson & Marmot 2006). Poor-quality housing has been associated with respiratory and cardiovascular problems, increased risk of injuries and worse mental health outcomes (Kanchongkittiphon *et al.* 2015; Midouhas *et al.* 2019; Nasim 2022; Simpson *et al.* 2024). These health risks do not occur in isolation but coincide with other environmental externalities: substandard housing is often located in areas with greater exposure to *environmental* hazards, less access to greenspace and higher concerns regarding neighbourhood safety (Cole *et al.* 2024).

There is growing evidence of a synergistic effect of outdoor air pollution and high ambient temperatures on health: several studies have found that hospital admissions during hot weather events rise with incremental increases in ambient concentrations of particulate matter ($PM_{2.5}$, PM_{10}) and nitrogen dioxide (NO_2) (Grigorieva & Lukyanets 2021; Yitshak-Sade *et al.* 2018). These studies tend to focus on outdoor exposure, with fewer considering the mediating impact buildings have on exposure to air pollution and high temperatures and the roles that dwelling design, ventilation, energy efficiency and insulation may have. For research quantifying the health impacts of *indoor* environmental exposures, studies typically rely on observational study designs using cohort or cross-sectional data (Midouhas *et al.* 2019; Nasim 2022) yielding sample sizes in the thousands which require large time and resource commitments and may be prone to selection bias (Schoeler *et al.* 2023).

Alongside these dual environmental pressures on health are additional social pressures and policy considerations. There is a need to reduce heating costs as domestic energy prices have risen, leaving 30% of UK households spending more than 10% of their net income on energy in 2022 (Bradshaw & Keung 2022; DESNZ 2023). The housing stock must also meet national net zero targets (BEIS 2020). While those experiencing fuel poverty have been shown to benefit most from dwelling energy-efficiency improvements (Kerr *et al.* 2017), there may be unintended consequences associated with improving the energy efficiency of a dwelling. For example, increasing the insulation and airtightness of buildings improves energy efficiency and health in winter, but may increase the risk of summer thermal discomfort if done without the compensatory measures (Mavrogianni *et al.* 2013; Ortiz *et al.* 2020; Porritt *et al.* 2013), and indoor concentrations of some pollutants, as well as damp and mould, have been found to increase following some retrofits (Shrubsole *et al.* 2016). However, some studies have reported no effect on overheating of energy-efficiency improvements, including wall insulation, and a reduction in overheating in dwellings with thicker loft insulation (Fosas *et al.* 2018; Lomas *et al.* 2021, 2024). It may be that energy-efficient buildings being found to overheat more is due to studies conflating energy efficiency with built form. For example, newer more energy-efficient buildings are often flats, which often overheat more. This has relevance when considering inequalities in exposure as low-income households are more likely to occupy flats, so may therefore experience higher indoor temperatures. These complex interactions between different housing characteristics and outdoor conditions require that dwelling improvements are planned carefully whilst considering the potential for unintended consequences.

Many studies have examined how outdoor environmental exposures, especially heat (Chakraborty *et al.* 2019; Cole *et al.* 2024; Macintyre *et al.* 2018) and air pollution (Milojevic *et al.* 2017), have an inequitable distribution across the population; especially that outdoor air pollution and extreme temperatures can be, on average, higher in more economically disadvantaged areas within cities. Studies of the urban heat island effect have demonstrated how flats (which are thought to be more likely to overheat) are often located in the hottest areas of a city (Macintyre *et al.* 2018). Some studies frame this as an environmental justice issue, arguing that disadvantaged groups bear a disproportionate burden of exposure to environmental hazards (Pearce *et al.* 2010). However, these studies have usually relied on outdoor environmental exposure estimates due to the sparsity of indoor monitored data.

Another strand of research has sought to fill gaps in the data relating to indoor overheating and air pollution concentrations using building stock models. Models of archetypal buildings have been used to explore what features of a residential building may cause it to overheat (Mavrogianni *et al.* 2014; Oikonomou *et al.* 2012). Studies have demonstrated how building energy simulation can be scaled to a large building stock using a meta model (see the Methods section) to predict indoor temperatures and indoor air pollution concentrations (Symonds *et al.* 2016) and can be applied to a spatialised housing stock based on Energy Performance Certificate (EPC) data (Taylor *et al.* 2019). Taylor *et al.* (2016) combined data from the Homes Energy Efficiency Database (HEED)—a database containing records of government-funded energy-efficiency installations in the UK housing stock—with data from the English Housing Survey (EHS) to create a spatially distributed housing stock to which building energy modelling was applied. Indoor overheating metrics and ratios of indoor to outdoor pollution were estimated. The study found that buildings in urban (as opposed to rural) areas had higher mean summertime daily maximum daytime living room temperatures and lower indoor–outdoor pollution concentration ratios, driven mainly by differences between flats and houses. However, this study did not include variations in the outdoor environment. Recent work has demonstrated how area-aggregated EPC data linked to administrative data can be informative for health studies (Simpson *et al.* 2024). This approach allows the integration of information about built form, building materials and airtightness—which are more readily available, less intrusive and resource intensive to collect—to estimate indoor conditions; but has the limitation that the results are dependent upon the modelling assumptions and accuracy of the available data.

This technique has also been used to explore disparities in exposure to indoor air pollution by linking spatialised predictions of indoor air pollution with administrative data, finding that modelled infiltration of outside sourced air pollution into buildings was lower in more deprived areas of Greater London, but that modelled indoor concentrations from outdoor sources remained higher due to elevated ambient concentrations in such areas. Others have noted that urban flats may have reduced infiltration of outdoor-source $PM_{2.5}$ due to lower permeability and being sheltered by adjoining buildings (Taylor *et al.* 2014). Additionally, population subgroups with an elevated risk of developing health impacts following exposure to high indoor temperatures and air pollution concentrations may spend an increased amount of time at home, indoors, relative to the wider population, making the home environment especially important (Ferguson *et al.* 2021; Holgate *et al.* 2021).

This paper uses building modelling, outdoor spatial data for temperature and $PM_{2.5}$, and area-level socio-economic data to identify inequalities in indoor exposure to heat and poor air quality, and their drivers at the building level. This advances on previous work that focuses on single indoor exposures by considering the two, often co-located, exposures (high temperature and air pollution) in parallel, and by exploring how these are driven by both the outdoor conditions and dwelling characteristics. Coverage of buildings is improved compared with the building stock used previously (Ferguson *et al.* 2021, 2023). Additionally, the inequalities of these exposures are assessed for a variety of different demographic variables, expanding on previous work which used income and the index of multiple deprivation (IMD) (Ferguson *et al.* 2021).

In this study 'indoor exposure' refers to the modelled temperature or $PM_{2.5}$ concentration an individual would be exposed to across the spatialised housing stock and does not take into account temporal differences in these conditions or differences in the times when individuals may be at home.

DOI: 10.5334/bc.425

2. METHODS

A general outline of the method is as follows, with detail given in the subsequent discussion, and Figure 1 provides a visual outline of the framework. Population exposure to indoor temperature and air pollution is assessed using the following metrics (the 'indoor exposures'):

- the two-day average daily-maximum living room temperature between the hours of 10:00 and 22:00 (Taylor *et al.* 2021)
- the annual average indoor concentration of $PM_{2.5}$ from *outdoor* sources.

The procedure used to estimate these exposures is now outlined.

First, building modelling tools are used to estimate the relationships between indoor and outdoor temperature, and between indoor and outdoor air pollution concentration, in residential buildings, including their dependence on building characteristics. The relationship between indoor and outdoor air pollution is characterised by an infiltration factor, defined as the ratio between the simulated indoor concentration of an outdoor-sourced pollutant and its concentration outdoors. The infiltration factor takes a value between 0 and 1, where 1 indicates that the air pollution concentration indoors is equivalent to the concentration outdoors, and 0 indicates no indoor pollution from outdoor sources. The indoor temperature was estimated for a given outdoor temperature, then outdoor temperature data were used in the later stage to reconstruct the indoor temperature distribution spatially.

Second, the distribution of building characteristics in the residential building stock across English and Welsh output areas (OAs—the smallest census geographical unit containing 40–250 households) is estimated from the EPC database (DLUHC 2023).

Third, annual average outdoor $PM_{2.5}$ concentrations and maximum temperatures (the 'outdoor exposures') for 2018 are extracted from existing spatial datasets: those of the Department of Environment, Food and Rural Affairs (DEFRA) (2018) and the Met Office's HadUK-Grid (Met Office 2018), respectively, for each OA. These three elements are combined to estimate indoor temperature and indoor concentration of outdoor-source $PM_{2.5}$ for each OA, which are linked to OA-level socio-demographic data from the most recent census.

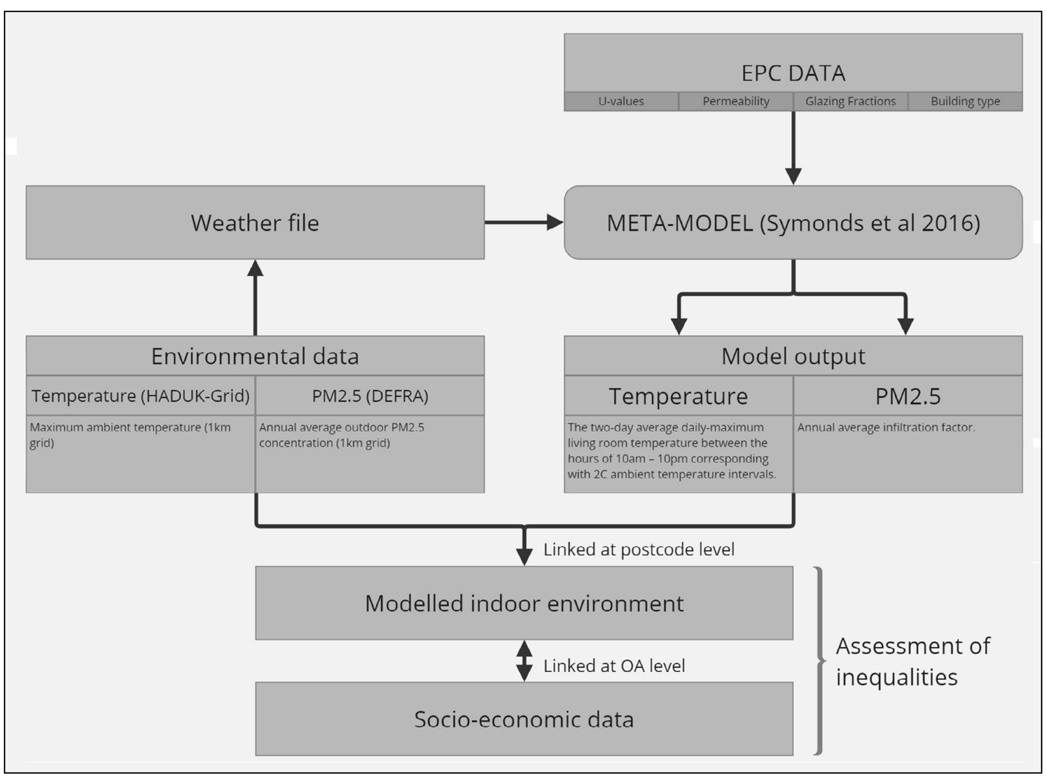

Figure 1: Outline of the stages of the framework described in the Methods section.

Note: Building stock modelling and environmental data are linked to estimate area-level indoor exposures. The indoor exposures are further linked to socio-demographic data to assess inequalities in their distribution.

Finally, these linked, OA-level data are used to estimate distributions of indoor temperature and indoor concentrations of outdoor-source $PM_{2.5}$ concentrations weighted by the frequency of different socio-demographic populations in each OA in England and Wales. This output informs the present assessment of inequalities in indoor exposures.

2.1 BUILDING SIMULATION

Building simulations were run in EnergyPlus (v8.8), which is a widely used and well-validated building energy simulation program based on fundamental heat-balance principles. Heat balance of zones (rooms) and building elements (walls, roof, windows, *etc.*) are solved using the finite difference method, including the effect of solar gains, internal gains and assumed occupant behaviour. EnergyPlus includes an air flow network model that calculates the transfer of air between building zones and the outdoors, and can estimate pollutant concentrations using balance equations. Air flow is fully coupled to the thermal model and includes the effect of window-opening behaviour. A fixed outdoor concentration of an air pollutant is assumed, as well as a rate of deposition on building surfaces, which leads the pollutant concentration to decrease over time in the absence of other exchanges. Therefore, a more airtight building produces a lower modelled average concentration of air pollutants from outdoor sources. The authors chose not to model indoor sources of air pollution in this study, as its emphasis is on the modification of outdoor environmental exposure data by buildings.

To scale the analysis to the large number of buildings described by the EPC data, a meta-model approach was used following Symonds *et al.* (2016). A sample of building simulations was generated for a set of archetypical buildings with input parameters sampled randomly according to a Latin-hypercube design of experiment. The design of experiment maximises the information extracted from a sample of the input space given that a full factorial experiment is too computationally expensive. The input–output relationship produced by the physical models was summarised using an artificial neural network (ANN) model; this is called a meta-model because it is a model of models. The purpose of the meta-model is to interpolate the results from different building simulations to a given combination of input variables; this is more computationally efficient than running building energy simulations for all possible buildings and produces only a small loss in accuracy (Symonds *et al.* 2016). The ANN was chosen because it has been shown to perform well at this task (Symonds *et al.* 2015). The meta-model was then used to estimate efficiently the distribution of outdoor source pollutant infiltration and indoor temperature across the building stock.

Input parameters for the building simulation include the window, wall, roof and floor thermal transmittances (often referred to as the '*U*-value'), overall building permeability, orientation, occupant window-opening threshold and occupant thermostat-setting. Categorical input variables include the building archetype and wall type (solid/cavity). Eight building archetypes were used, namely: detached house, semi-detached house, bungalow (*i.e.* single-storey detached house), mid-terrace house (*i.e.* row-house), end-terrace house, high-rise flat, low-rise flat and converted flat. These archetypes were previously developed by Taylor *et al.* (2019) and represent about 75% of the existing English housing stock.

2.2 BUILDING STOCK INFORMATION

Building stock information was extracted from the EPC database (DLUHC 2023), expanding on the method used by Taylor *et al.* (2019). An earlier study used the HEED and EHS datasets (Taylor *et al.* 2016), which may be higher quality data, but HEED covers fewer buildings and the EHS is not open data. EPCs describe the expected energy performance of buildings, and are required for all buildings built, sold or rented since the introduction of the EPC policy in 2008. Information indicates the type of building: *U*-values (thermal transmittances) of the glazing, roof, exterior walls and ground floor; floor area, ceiling height and glazing fraction. The extracted EPC stock dataset covers 17,770,964 dwellings, with EPCs recorded between 1 October 2008 and 31 May 2023 (date of download). EPCs were used because they offer the most complete and up-to-date open public source of building information, and are geolocated so they can be combined with other spatial data.

Following Taylor *et al.* (2019), permeability, *U*-values and glazing fraction were estimated based on the EPC. Permeability was estimated based on the presence of open fireplaces and the main heating system in place, type of building, facade area, whether floors are solid or suspended, building materials and glazing type. Infiltration through each of these elements was estimated according to Standard Assessment Procedure (SAP) ventilation rate calculations and summed as per SAP, accounting for the following assumptions: double-, secondary- and triple-glazed windows were assumed to have draught-proofing, the extent to which varied according to a three-point scale indicating the window had 'some', 'partial' or 'mostly' draught-proofing. Suspended timber ground floors were assumed to be unsealed if built before 1975 and sealed thereafter. Dwellings that indicated solid fuel, gas or anthracite as the main heating fuel were assumed to have an open flue, and flats and maisonettes were assumed to have a draught lobby, whilst other dwelling types were not. Open EPC data only record whether glazing fractions are typical for the building type (five-point scale from 'Much less than typical' to 'Much more than typical'), so glazing fractions were estimated based on percentiles extracted from the EHS for each building type and region. Glazing fraction was assumed to be equal on all glazed facades of the building. When a building had been surveyed more than once, data were taken from the latest EPC, but missing data were infilled where possible from superseded EPCs. To ensure high data quality, unrealistic values were removed (*e.g.* unrealistically small or large floor areas and ceiling heights).

Each EPC contains the postcode of the building it describes. The postcode was used to link to the aggregation areas used for the other data sources (OA, *etc.*) with a look-up table provided by the UK Office for National Statistics (ONS).

Changes were made to the previous method (Taylor *et al.* 2019) to improve the coverage and accuracy of the classification:

- Thermal transmittances (*U*-values) were extracted directly from the EPC where available, or estimated depending on the performance and/or thickness of reported insulation (mm). If the insulation thickness was missing, the age band of the dwelling and the classification of the building element based on keywords (*e.g.* 'pitched', 'flat', or 'thatched' for roofs, and 'cavity', 'solid brick' or 'timber' for external walls) was used to assign a *U*-value based on look-up tables provided in SAP for roof and wall elements. Floor *U*-values were calculated using the method provided in SAP. Estimated roof, wall and floor *U*-values were internally validated against the energy-efficiency rating additionally recorded in the EPC database for the corresponding building element. These variables assign a rating along a five-point scale (from 'Very poor' to 'Very good') on which each corresponds to a numerical *U*-value range (BRE 2014). If estimated *U*-values fell outside this range, they were assumed to be erroneous and a *U*-value within the given range was randomly selected from a uniform distribution. Previous work only used the efficiency category.
- Distinctions between high- and low-rise, purpose-built and converted flats are not directly recorded in EPCs. Previous work using EPC data assumed that a flat was converted if the 'built form' field of the EPC identified it as a house; the authors identified that this was inaccurate for many buildings and that the built form field may simply be filled with a default value in many cases. Therefore, a new method of distinguishing between types of flat with increased accuracy was developed. It was assumed that flats are high rise if part of a building has seven or more storeys, or if the first line of its address ends in 'Point', 'Tower' or 'Heights'. Flats were assumed to be purpose-built low-rise if not high-rise and if the first line of its address ended in 'Mansions', 'Court', 'Flats' or 'Apartments' and did not begin with an alphanumeric, which usually indicates a modified address (*e.g.* '1A'). Otherwise, flats were assumed to be converted rather than purpose-built.
- Remaining missing data were infilled using medians grouped by building type and OA.

No information was included in the building stock describing occupant behaviour, so thermostat set points and window-opening thresholds had assumed distributions. Heating set points were assumed to have a truncated normal distribution with a mean of 22°C, standard deviation (SD) of 3°C, and truncated at 15 and 26°C. Window-opening thresholds were also assumed to have a truncated normal distribution with a mean of 24°C, SD of 5°C and truncated at 10°C. Windows were assumed to open if the indoor temperature was higher than the outdoor temperature, the room was occupied, and the indoor temperature was above the threshold. The values were sampled for the building energy modelling step, but not used as predictors for the meta-model step, so the distributions contribute to the error estimate of the meta-model but are effectively averaged out of the final prediction. Window-opening contributes to the transport of outdoor pollutants into the building. No information about the internal subdivision of buildings is included in the EPC data, so all buildings of the same archetype were assumed to have the same layout scaled according to the total floor area reported in the EPC database. No information on building orientation was included in the database, so buildings were assigned orientations from a random uniform distribution; this makes predictions for individual buildings and streets inaccurate but will not affect the accuracy when averaging over larger areas. As no information existed about external shading of windows with brise soleil or external shutters, it was assumed that none was present. Internal drapes were included, active between 22.00 and 08.00 hours for privacy/lighting purposes.

2.3 OUTDOOR ENVIRONMENTAL DATA

Outdoor temperature observations were used from summer 2018, which had the highest UK June–August average temperature recorded at the time. Maximum outdoor temperature during August 2018 was extracted from the Met Office's HadUK-Grid 1-km-scale dataset (Hollis *et al.* 2019) at each postcode centre point and used as the input temperature for the meta-model to estimate the indoor temperature for each dwelling. HadUK-Grid is a gridded data product created by re-analysis of weather station network observations. Annual average outdoor $PM_{2.5}$ concentration from DEFRA's background mapping project at 1-km grid level for each postcode centre point was extracted. These are modelled based on road network, industry and rail information, and observations from a national monitoring network. The 2018 estimates were used to correspond to the period chosen for the temperature analysis. To estimate indoor concentrations of outdoor-source $PM_{2.5}$, outdoor $PM_{2.5}$ concentration was multiplied by the annual average infiltration factor for each dwelling, estimated by the meta-model. Each postcode approximately maps to a single OA, described by a look-up table from the ONS.[1] These datasets were chosen as the best available open public spatial data. Annual average $PM_{2.5}$ concentration was used because temporally disaggregated spatial data covering the study area were not available from an appropriate open source.

2.4 ANALYSIS

The distribution of indoor heat and air pollution across the population, in relation to income, ethnicity and age, including older adults and infants, was assessed. Data relating to ethnicity and age are included in the most recent census, conducted in 2021, at census OA level. The recipients of Universal Credit, a means-tested social security payment available from the UK Department of Working Pensions (DWP) (2023), were used as a proxy of low-income households at OA level. The meta-model, initialised and run as outlined above, outputs information on the indoor conditions of each dwelling, including the indoor temperature over a range of outdoor temperatures and infiltration factors. This information was linked to postcode level data for the 90th percentile of daily maximum temperature for the summer and outdoor concentrations of $PM_{2.5}$ to estimate the indoor conditions for each dwelling. This outputs the indoor modelled indoor conditions for high temperatures and an annual average indoor concentration of $PM_{2.5}$. Descriptive analysis of the estimated indoor conditions, potential drivers and area measures of socio-economic indicators was undertaken to explore the variation of indoor exposure across these dual environmental hazards. A summary of the datasets used in the modelling and subsequent analysis is included in Table 1. Differences in the distributions of outdoor and indoor exposures were compared using histograms, box plots and maps. Correlation coefficients, which describe the strength of association between two variables, were used to assess to what extent the dwellings in areas with higher outdoor temperatures and $PM_{2.5}$ concentrations were the same dwellings with higher indoor temperatures and $PM_{2.5}$ concentrations. Specifically, Spearman's rank correlation coefficients were calculated for indoor against outdoor temperature and for indoor against outdoor $PM_{2.5}$ for each dwelling. Spearman's rank correlation indicates whether the relationship between two variables is monotonic on a scale of 0 to 1 (1 = perfect positive monotonic).

MODEL COMPONENT	DATA	DEFINITION	SOURCES
Housing stock meta-model	Dwelling Energy Performance Certificate (EPC)	Buildings database describing the quality of building features and fabric efficiency	DLUHC (2023)
Outdoor environmental conditions	Outdoor $PM_{2.5}$ concentrations	Annual average outdoor $PM_{2.5}$ (particulate matter) concentration in a 1 × 1 km grid for England and Wales	DEFRA (2018)
	Outdoor temperature data	Summer (June–August) 90th percentile of daily maximum temperature for 2018 from the HadUK-Grid	Hollis *et al.* (2019)
Vulnerability analysis	Individuals aged ≥ 65 years	Frequency of the population aged ≥ 65 years by census output area (OA)	ONS (2021)
	Children/infants	Frequency of the population aged 0–4 years by census OA	ONS (2021)
	Ethnic minority	Frequency of the population belonging to a racial or ethnic group outside of the majority white British population of the UK by census OA	ONS (2022)
	Low income	Frequency of individuals in receipt of Universal Credit per census OA	DWP (2023)

Table 1: Summary of the datasets used in the model and analysis.

3. RESULTS

3.1 DIFFERENCES IN OUTDOOR CONDITIONS ACROSS SOCIO-ECONOMIC GROUPS

Figures 2a and 3a show the population-weighted distributions of outdoor temperature and outdoor $PM_{2.5}$ concentration. For both environmental hazards there is a pronounced difference in the distributions for the ethnic minority and ethnic non-minority populations. Smaller differences between the other demographic groups can be seen in the outdoor temperature and outdoor $PM_{2.5}$ distributions for the remaining population groups: infants, people < 65 years and low-income households have slightly higher outdoor exposures. The urban heat island effect and poorer air quality found in cities mean that exposures to these environmental hazards are more pronounced in urban areas. Differences in exposure between demographic groups are then driven by the distribution of those groups between more and less urbanised areas (and especially London): with a higher proportion of ethnic minority people, and a higher proportion of people < 65 years (ONS 2023).

For temperature, a Spearman's rank correlation coefficient of 0.61 was recorded, and for $PM_{2.5}$ concentration, 0.69, both significant at the 1% level. This demonstrates how the modelled variations in dwelling indoor temperatures and outdoor sourced $PM_{2.5}$ are strongly driven by variations in outdoor conditions, but that there is also substantial variation created by building characteristics that modify outdoor–indoor transport. This means that the buildings with the highest indoor temperatures and outdoor-sourced $PM_{2.5}$ indoor concentrations are often, but not always, those in areas with the highest outdoor temperatures and outdoor $PM_{2.5}$ concentrations.

3.2 DIFFERENCES IN HOUSING AS A DRIVER ACROSS SOCIO-ECONOMIC GROUPS

Figures 2b and 3b present the impact of the dwelling characteristics separated from the outdoor conditions by estimating indoor temperature for a single daily maximum outdoor temperature (26°C chosen as a high but not extreme temperature allowing for reliable modelling) and calculating the dwellings' outdoor pollutant infiltration factor. This summarises the effect of residential buildings on exposure to heat and outdoor $PM_{2.5}$ under fixed outdoor conditions.

Dwellings in areas with greater proportions of infants, people < 65 years, low-income households and ethnic minorities are warmer (at a fixed outdoor temperature of 26°C) (Figure 3b). Dwellings in areas with greater proportions of low-income households and ethnic minorities have higher infiltration factors and are therefore more prone to higher levels of indoor air pollution from outdoor sources.

Figure 4 shows the spatial distributions of the environmental hazards and the modifying effect of dwellings at local authority district (LAD) level. LAD level is used here for visualisation purposes as there are about 200,000 OAs and about 400 LADs in England and Wales. Dark brown areas represent a co-location of a hazard and dwellings which exacerbate exposure indoors. For both environmental hazards, the South East of England has the highest outdoor levels. However, dwellings that exhibit greater warming and higher infiltration factors can be seen across the South West, Wales and the North. Co-location is particularly prominent in London and the East coast. Both hazards have similar distributions across England and Wales.

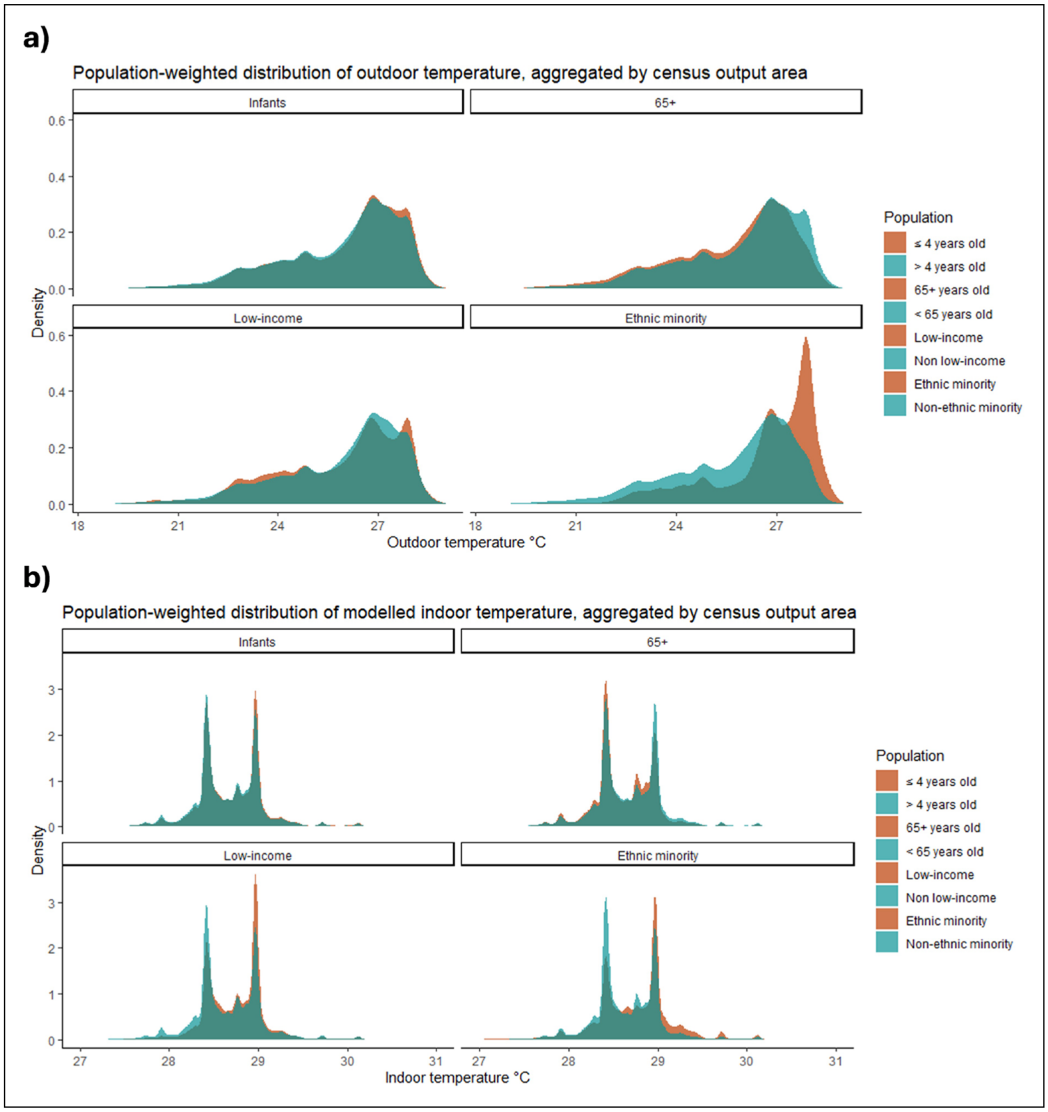

Figure 2: Differences in outdoor and indoor temperature across socio-economic groups: **(A)** population-weighted distributions of outdoor temperature for each population group; and **(B)** modelled indoor temperature for a constant outdoor temperature (26°C).

Note: Differences are plotted for a single outdoor temperature to separate the modifying effect of the buildings from outdoor conditions.

3.3 RESULTING DIFFERENCES IN INDOOR EXPOSURE

Figures 5 and 6 show the distribution of high indoor temperature and $PM_{2.5}$ exposure across socio-economic groups, respectively, by combining the dwelling and outdoor environmental information. Increased exposure to high indoor temperature and $PM_{2.5}$ can be seen in areas with greater proportions of infants and ethnic minorities. Additionally, areas with higher proportions of low-income households exhibit a slight increase in air pollution exposure with an uptick in the lowest decile, potentially corresponding to poorer air quality in more affluent city centres, such as Central London.

As the proportion of older adults increases, there is a reduction in indoor levels to both environmental hazards. Areas of high older adult populations tend to be less urban (see ***Figure S1*** in the supplemental data online), and this effect can be explained by the urban and rural effects in outdoor exposure, with urban areas being warmer and tending to have higher concentrations of $PM_{2.5}$.

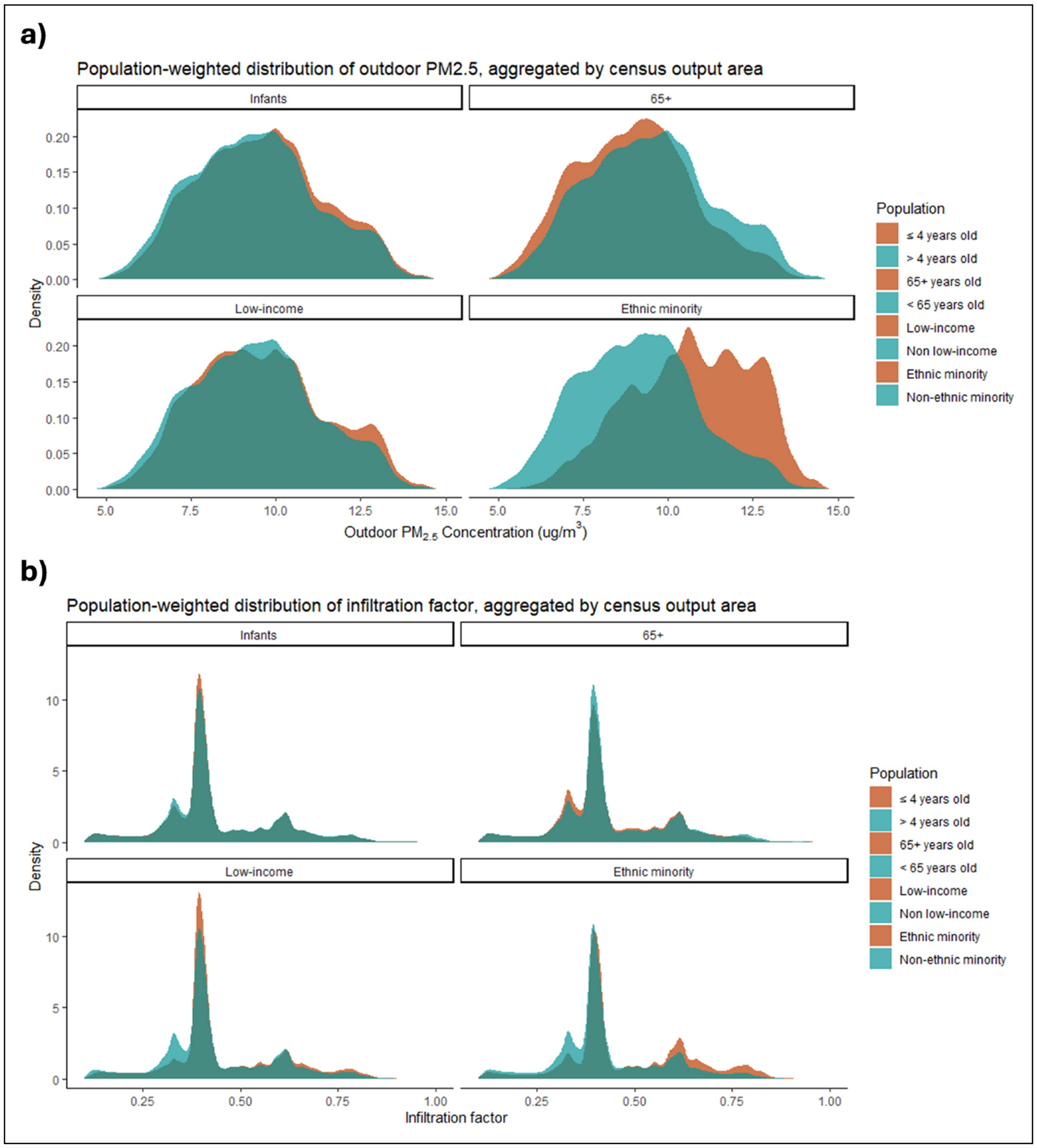

Figure 3: Differences in outdoor and indoor $PM_{2.5}$ across socio-economic groups: **(A)** population-weighted distributions of outdoor $PM_{2.5}$ concentration for each population group; and **(B)** infiltration factors for each population group.

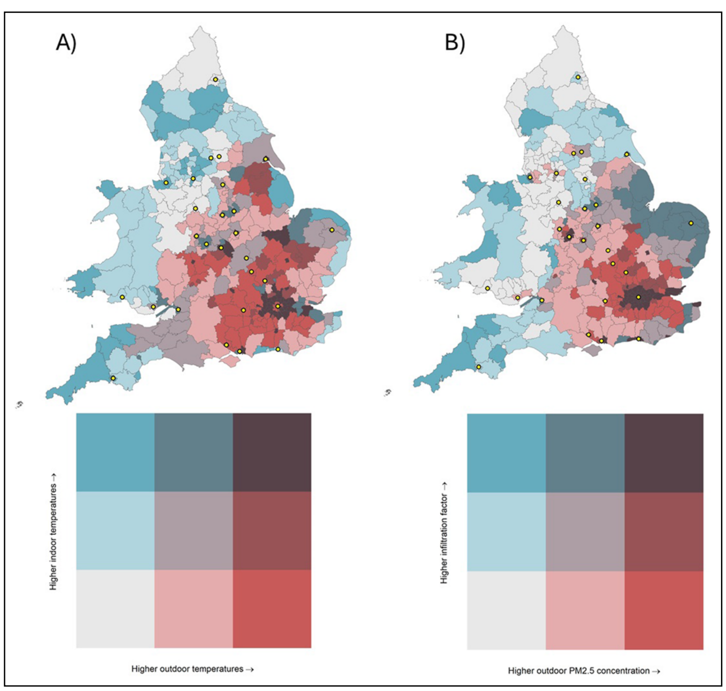

Figure 4: Bivariate maps showing the distribution of the environmental hazards (red scale) and the modifying effect of the dwellings (blue scale): **(A)** heat and **(B)** high $PM_{2.5}$ concentrations.

Note: (A) The outdoor temperature is the 2018 summer 90th percentiles averaged across local authority district (LAD). The indoor temperature is the average modelled indoor temperature for each LAD under a fixed outdoor temperature (26°C). (B) The outdoor $PM_{2.5}$ is the average 2018 outside concentration averaged across LAD. The infiltration factor is the modelled proportion of outdoor $PM_{2.5}$ that enters the dwelling.

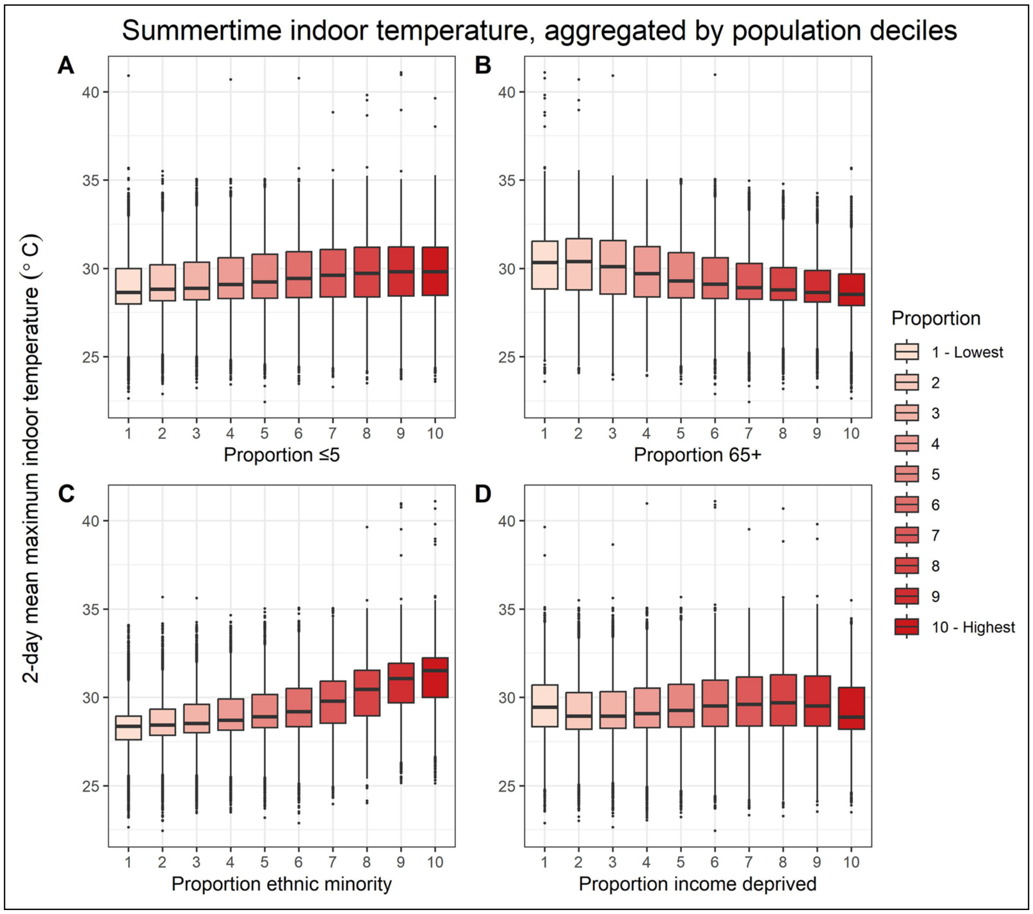

Figure 5: Differences in indoor temperature across socio-economic groups driven by a combination of outdoor conditions and dwelling characteristics.

Note: The *x*-axis represents the proportion of each socio-economic group as a decile, where 1 is the decile with the lowest proportion of each group and 10 is the highest. The *y*-axis represents an average of the modelled maximum two-day temperature calculated for buildings in each output area (OA) for the study period (summer 2018).

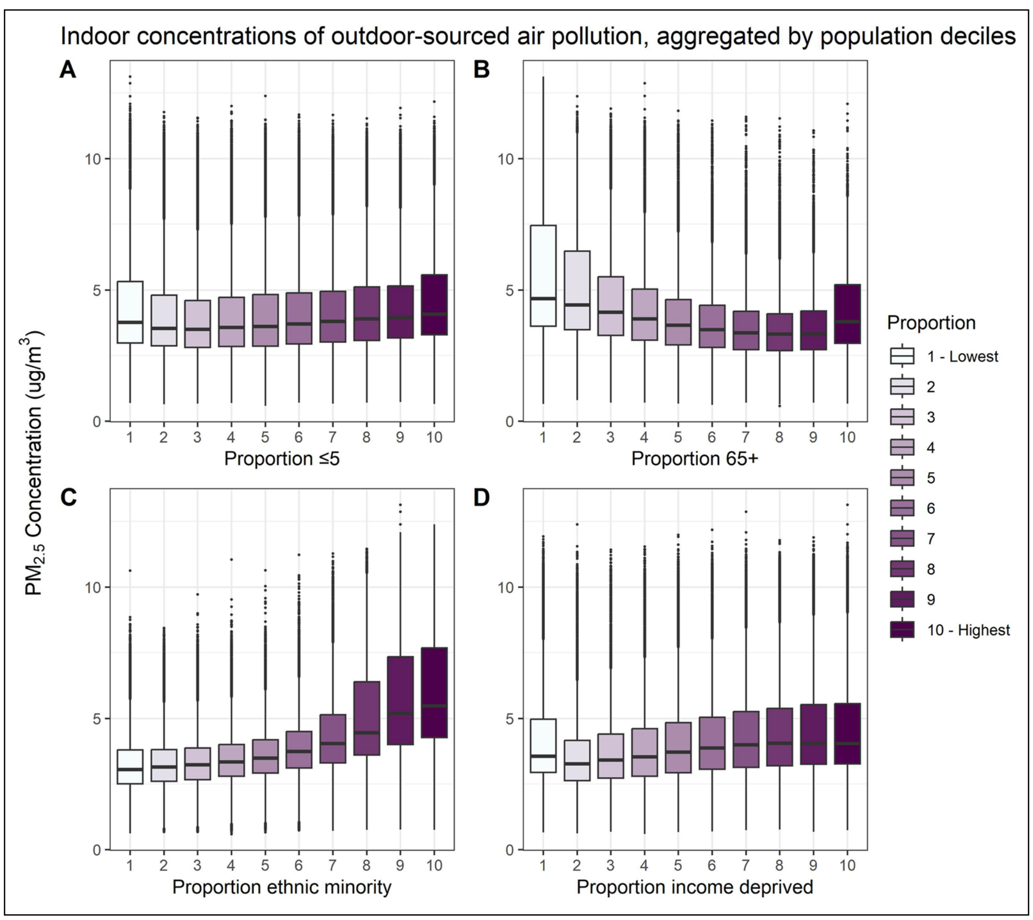

Figure 6: Differences in indoor $PM_{2.5}$ concentration across socio-economic groups driven by a combination of outdoor conditions and dwelling characteristics.

Note: The *x*-axis represents the proportion of each socio-economic group as a decile, where 1 is the decile with the lowest proportion of each group and 10 is the highest. The *y*-axis represents the modelled indoor $PM_{2.5}$ concentration calculated for buildings in each output area (OA) using the average outdoor concentration for 2018.

3.4 CO-LOCATION OF OVERHEATING AND POOR INDOOR AIR QUALITY

Figure 7 shows a bivariate choropleth map of England and Wales created using indoor $PM_{2.5}$ and temperature information at local authority level. Areas of co-location of high indoor temperature and indoor $PM_{2.5}$ from outdoor sources can be seen around many major cities (marked by yellow dots), with greater indoor levels generally found in the South and East of England. The East coast exhibits high exposure to indoor heat. High exposure to indoor $PM_{2.5}$ in the areas surrounding London may be due to the extensive road network feeding the city. Moderate levels of indoor heat are observed in the North Wales, Liverpool and Manchester region, despite low outdoor temperatures, and are driven primarily by housing factors (Figure 4). Rural areas, outside of the major towns and cities, in the South East also exhibit a moderate indoor heat; this is despite higher outdoor temperatures, suggesting a mediating effect of dwellings.

Figure S1 in the supplemental data online shows the distribution of the socio-economic variables for the same region and scale for context. Areas where high indoor temperature and low air quality coincide with vulnerable population groups can be identified and targeted for indoor monitoring initiatives and interventions aimed at reducing health inequalities by improving indoor conditions. Additional maps included in Figure 7 demonstrate the granularity of the data at a scale relevant to policymakers.

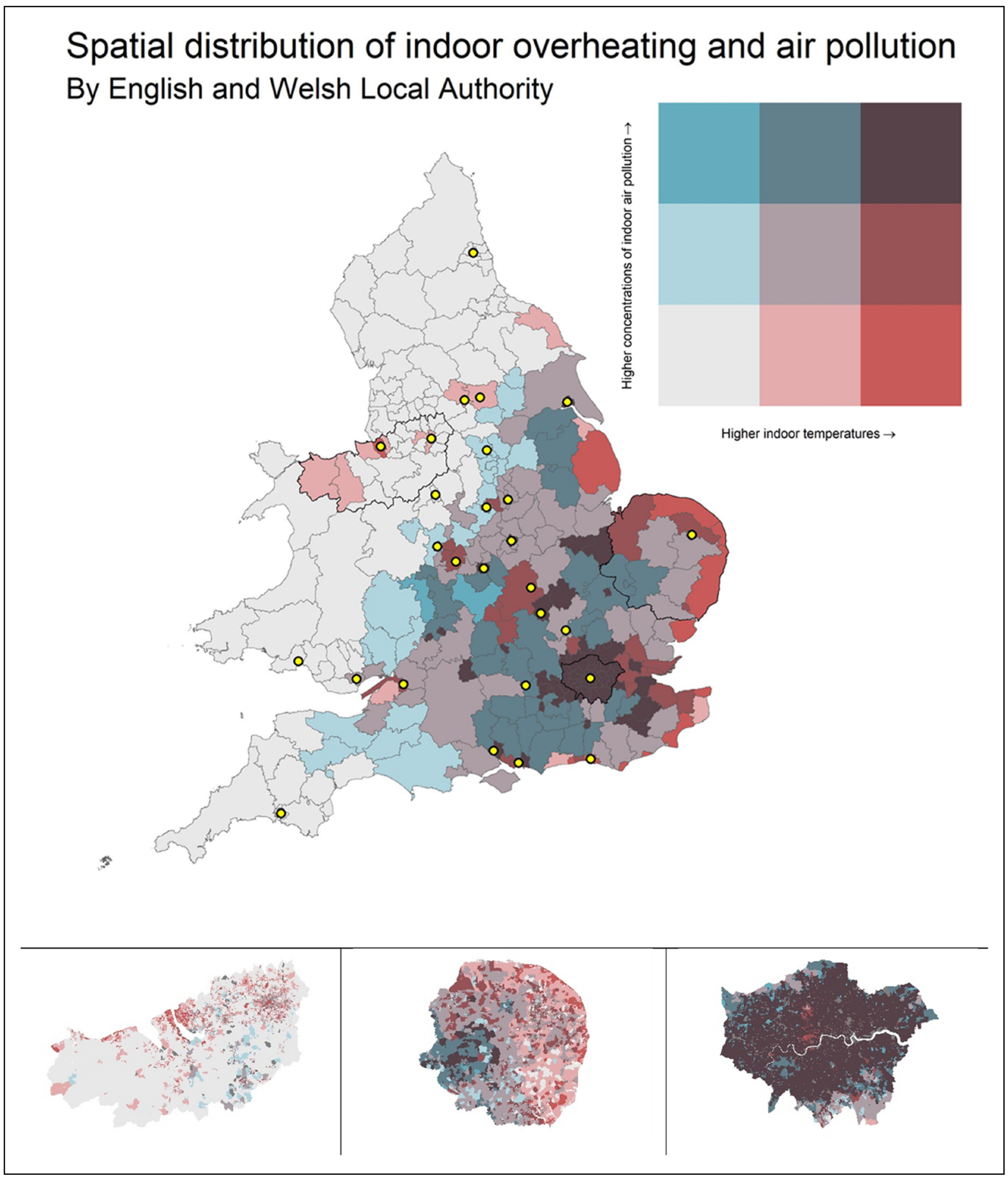

Figure 7: Bivariate choropleth map showing the spatial distribution of modelled indoor temperatures and $PM_{2.5}$ concentrations. The smaller scale maps at bottom demonstrate the spatial scale of the analysis. The regions selected—(from left to right) North Wales, Liverpool and Manchester region; North East Anglia; and London—are also outlined in the full map.

Note: Each region is assigned a colour on the scale depending on the tertile of indoor temperature and $PM_{2.5}$ concentration in which it falls. Dark brown areas represent high exposures (third tertile) to both indoor hazards. Yellow dots represent major cities (with populations over 200,000).

4. DISCUSSION

The framework presented in this study uses the EPC data alongside environmental datasets to estimate indoor exposures at the building level. These estimates were then linked to socio-economic data at high spatial resolution (the lowest census block), with each OA containing 40–250 households, to estimate inequalities in exposure. Indoor conditions were found to be driven both by outdoor conditions and modification by dwellings, and area-level inequalities exist across these drivers. This expands on previous methods that examined heat and air pollution separately or which did not explore their relation to demographics.

When implementing this framework for England and Wales, pronounced differences in high indoor temperature and $PM_{2.5}$ concentrations driven by outdoor sources were found for the ethnic minority population. Higher exposure to outdoor $PM_{2.5}$ can be seen in infant populations and low-income households compared with the population average. Higher indoor heat exposure driven by dwellings was found for infants, low-income households and ethnic minority populations. Higher infiltration factors of external pollutants were found in areas with greater proportions of low-income households and ethnic minorities. This resulted in greater overall exposure to indoor heat found in areas with larger ethnic minority and infant populations and greater exposure to indoor air pollution in areas with larger ethnic minority, low-income and infant populations. Areas with higher proportions of older adults had lower indoor exposure to both environmental hazards.

Co-occurrences of high indoor temperature and air pollution were identified in several regions, primarily larger cities in the South and East of England. Previous studies have found a coincidence between heat and air pollution events and compounding health impacts of the two exposures (Grigorieva & Lukyanets 2021; Rai *et al.* 2023; Stafoggia *et al.* 2023; Yitshak-Sade *et al.* 2018). Future work could build on the identification of areas where high temperatures, high air pollution and vulnerable populations co-occur to prioritise interventions that aim to reduce health inequalities. This could involve prioritisation for more expensive monitoring studies to aid policymakers. This work should include a parallel exploration of internally generated pollutants and a greater range of types of pollutant.

4.1 STRENGTHS AND LIMITATIONS

An extended framework is presented to estimate unequal exposure to indoor heat and air pollution at the national level using publicly available data. As the EPC dataset does not include details on occupant demographics, the framework presented here allows for the identification of unequal housing and environmental exposures for different population groups without the need for linked administrative data. This bypasses barriers associated with accessing and using administrative data, such as delays and costs in gaining access and the risk of personal data disclosure. This approach could be applied to other countries that have open EPC data (or similar), open demographic data and open data on environmental conditions.

The main limitation using area-level data is that there are nuances in the distribution within areas that will be lost when examining small areas or small numbers of buildings. For example, these results show how, over England and Wales, areas with higher proportions of ethnic minority residents often have higher indoor concentrations of $PM_{2.5}$ from outdoor sources; and this method could be used to identify areas which have both a high proportion of ethnic minority residents and high indoor concentrations of $PM_{2.5}$ from outdoor sources. However, this method does not indicate whether buildings with high indoor concentrations of $PM_{2.5}$ from outdoor sources within an area of aggregation are occupied by residents from any particular demographic. This is an inescapable limitation of using aggregated data.

The EPC database provides the most comprehensive open public data source of residential building characteristics; however, there are several limitations with EPC data. The register only began in 2008 and a property is entered when it is sold, constructed or let, meaning the database better represents newer, more energy-efficient properties. Older properties, located in areas with lower residential mobility, may therefore not be entered into the database, resulting in a significant portion of the housing stock being overlooked. There are also known errors with the existing database, relating to erroneously entered data (Few *et al.* 2023; Hardy & Glew 2019). Details on the orientation of each building are not included in the database, and were therefore uniformly assigned to each EPC dwelling, despite building orientation being a known contributor to overheating risk (Gupta & Gregg 2012; Habitzreuter *et al.* 2020). A previous study has shown that predicting overheating in a building based on incomplete information is challenging, but that performance is better at the stock level when averaging across many buildings (Symonds *et al.* 2017).

Modelled window-opening behaviour was simply based on temperature and the scheduled presence of a person, but research has shown that other factors can strongly influence window-opening behaviour, especially noise and security (Mavrogianni *et al.* 2017). This may mean that in reality windows are opened less near busy roads or in urban areas, which could decrease indoor air pollution from outdoor sources and increase indoor temperatures, respectively.

The building meta-model used eight static housing archetypes. Though these archetypes are considered broadly representative of the housing stock, they will not represent the full range of dwellings across England and Wales. Modifications to the dwelling geometry, such as the addition of conservatories and extensions, has not been considered. The framework uses population data at the lowest level of spatial aggregation available in the UK (census OA). However, census OAs located in densely populated areas, such as Greater London, may exhibit high levels of heterogeneity in building parameters, leading to the masking of effects when indoor environmental conditions are spatially aggregated. By looking at each building as a single unit, differences across a building may be missed, particularly in the case of flats, where top-floor flats are more prone to overheating than those on lower floors. Further, the frequency of individuals in receipt of Universal Credit was used as a proxy of low income at the census OA level since the UK census does not release area-income estimates at such high spatial resolution. Beginning in 2013, Universal Credit replaced six existing benefit schemes and has faced criticisms due to its increased conditionality for eligibility, meaning claimants of the previous benefit schemes were no longer entitled to the payment. The use of Universal Credit as a proxy for low income may therefore not fully capture the extent of income deprivation across England and Wales, explaining why smaller differences in indoor $PM_{2.5}$ exposure were observed between low- and non-low-income residents in the framework presented here compared with previous work (Shrubsole *et al.* 2016). This difference could also be due in part to the inclusion of air pollution from indoor sources, including socio-economic differences in smoking rates. Indoor sources of air pollution are also important, but they were not modelled in the present study.

5. CONCLUSIONS

The framework outlined in this study enabled the estimation of indoor exposures and their distribution across population groups at the output area (OA) level for England and Wales. Using the Energy Performance Certificate (EPC) data and metamodel allowed indoor conditions to be estimated for about 15 million dwellings. Higher temperatures for dwellings were found in areas with larger infant and ethnic minority areas, and higher $PM_{2.5}$ concentrations for dwellings were found in areas with larger infant, ethnic minority and low-income populations, when compared with the population average. These differences in indoor exposure were driven by both the outdoor conditions and the modifying effect of dwellings. Co-location of indoor exposures was identified in the South East region of England and in urban areas.

Further work would extend this framework to include indoor sourced air pollution. The results can be used to identify areas of co-location of indoor exposures for targeted interventions which reduce inequalities. Separation of the environmental and building drivers of indoor exposures can be used to inform these interventions and ensure multiple exposures are considered to minimise the unintended consequences of building improvements.

NOTE

1 See https://geoportal.statistics.gov.uk/datasets/b7103ec863b741e99cd3720480dae932/about/.

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COMPETING INTERESTS

The authors have no competing interests to declare. This study was submitted to a special issue for which Anna Mavrogianni (co-author on this paper) acted as a guest editor. Anna Mavrogianni was recused from making any editorial decisions about this manuscript.

DATA ACCESSIBILITY

All data used in this analysis are open public datasets.

FUNDING

The authors' research is partly funded by the National Institute for Health Research (NIHR 200909) Health Protection Research Unit in Environmental Change, a partnership between the UK Health Security Agency (UKHSA) and the London School of Hygiene and Tropical Medicine, University College London, and the Met Office. The views expressed are those of the authors alone and not necessarily those of the NIHR, the UKHSA or the Department of Health and Social Care. CH is supported by a NERC fellowship (grant number NE/R01440X/1). CS and CH acknowledge funding from the Wellcome Trust HEROIC project (grant number 216035/Z/19/Z). JT acknowledges funding from the European Union NextGenerationEU instrument via the Academy of Finland (grant number 353327).

SUPPLEMENTAL DATA

Supplemental data for this article can be accessed at: https://doi.org/10.5334/bc.425.s1

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TO CITE THIS ARTICLE:
Cole, R., Simpson, C. H., Ferguson, L., Symonds, P., Taylor, J., Heaviside, C., Murage, P., Macintyre, H. L., Hajat, S., Mavrogianni, A., & Davies, M. (2024). A population-level framework to estimate unequal exposure to indoor heat and air pollution. *Buildings and Cities*, 5(1), pp. 562–580. DOI: https://doi.org/10.5334/bc.425

Submitted: 27 January 2024
Accepted: 14 October 2024
Published: 30 October 2024